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Exploiting Option Information in the Equity Market

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Public option market information contains exploitable information for equity investors for an investable universe of liquid large-cap stocks. Strategies based on several option measures predict returns and alphas on the underlying stock. Transaction costs are an important factor given the high turnover of these strategies, but significant net alphas can be obtained when using a simple approach that reduces transaction costs. These findings suggest that information diffuses gradually from the option market into the underlying stock market.

In our study, we examined whether public information in the option market predicts cross-sectional stock returns for a well-investable universe of highly liquid U.S. large-cap stocks and thus provides valuable, exploitable information for equity investors. Equity options have become an increasingly popular investment alternative over the past decades. They have asymmetric payoff characteristics and allow investors to take highly leveraged positions, making them important instruments for speculation or hedging. Options afford investors a view of the price development and risk of the underlying stocks. In fact, option prices reflect the expectations and worries that investors have about future stock price developments. Therefore, many practitioners view the equity option market as a primary source of information about the expected return, risk, and sentiment of individual stocks and the equity market in general. The question is whether this public information also provides valuable information to investors. That is, can investors exploit this information?

Standard economic theory suggests not. In complete markets, options are redundant securities and the public information they contain should already be reflected in the prices of other assets. Moreover, in efficient markets, stock prices should adjust immediately to public information. However, empirical research and intuition suggest otherwise. Empirical studies have generally found that options are nonredundant securities (see, e.g., Buraschi and Jackwerth 2001). Intuitively, the option market may lead the equity market if an investor with positive or negative information on a stock chooses to invest in the option market rather than in the stock itself. For example, Black (1975) argued that traders prefer to exploit private information by trading in the option market because the option market provides reduced transaction costs, increased financial leverage, and a lack of short-selling constraints. If equity market investors fail to trade on this information, a lead–lag relationship will emerge between the option market and the stock market. In fact, Hong and Stein (1999) argued that information diffuses gradually into and across markets, which was empirically confirmed by Hong, Torous, and Valkanov (2007).[1] Similarly, Chakravarty, Gulen, and Mayhew (2004) found that the equity option market contains information that is later reflected in stock prices. These findings suggest that publicly available information in the option market affects future stock prices, enabling stock return predictability.

Indeed, several recent studies have proposed option market measures that contain economically and statistically significant information for subsequent returns on the associated stocks. Xing, Zhang, and Zhao (2010) used the difference between the implied volatilities of out-of-the-money put options and at-the-money call options, commonly referred to as the out-of-the-money volatility skew, a measure that reflects the (informed) worries investors have about negative price

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movements. They found that stocks with the largest skew underperform stocks with the smallest skew. Bali and Hovakimian (2009) and Goyal and Saretto (2009) used the difference between realized and implied volatilities, a measure that captures the volatility risk of a stock. They found that a strategy that buys stocks with the lowest realized versus implied volatility spread and that shorts stocks with the highest spread produces significant positive returns. Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) used the spread between implied volatilities of at-the-money put versus call options, also known as the at-the-money volatility skew, which they argued captures the trading activity of informed investors and *jump risk*. Stocks with a low spread (i.e., stocks that have higher call than put implied volatilities) outperform stocks with a high spread. In addition, Cremers and Weinbaum (2010) used the recent change in the spread between the implied volatilities of at-the-money put and call options, which might capture the change in informed trading, and found a negative relation with stock returns.

These studies revealed the strong predictive power of public option market information for stock returns over 1996–2005. However, they all focused on a broad universe of stocks, which might not be exploitable for most practitioners owing to their liquidity constraints and needs. Moreover, these studies did not analyze the impact of transaction costs on profitability. Some of the studies also showed a declining performance toward the end of their samples and omitted the highly volatile period around the subprime crisis, a time when many equity funds were closed. Given the relatively short sample period of the studies on this topic, these extra years are highly relevant. Hence, from a practitioner's perspective, the value added by these studies remains unclear.

In our study, we examined whether these four measures—out-of-the-money volatility skew, realized versus implied volatility spread, at-the-money volatility skew, and the change in the at-the-money volatility skew—provide valuable information that is exploitable by equity investors. To that end, we (1) studied these strategies with respect to a well-investable universe of U.S. large caps (i.e., the stocks that practitioners find most attractive owing to their liquidity), (2) extended the sample to include the recent, volatile crisis period, (3) examined the combined predictive power of the four variables in an integrated option information strategy (from a practitioner's perspective, it is important to know whether performance improves when the variables are combined), and (4) thoroughly analyzed the impact of transaction costs. In addition, we examined the robustness of the option information strategy in various market conditions, as well as its interaction with information uncertainty.

■ *Discussion of findings.* We found that publicly available information in the option market is relevant for equity investors. In a well-investable universe of liquid large caps, trading strategies based on the out-of-the-money volatility skew, realized versus implied volatility spread, at-the-money volatility skew, and the change in the at-the-money volatility skew all yield significant returns and alphas. Although some studies have reported that the predictive power decreases over time until 2004–2005, we also found significant returns in the recent crisis years, which can serve as out-of-sample evidence. Combining all four variables into an option information strategy yields even larger profit opportunities of 10% a year for the long–short portfolio, thereby strengthening the relevance for equity investors of the publicly available information contained in option prices. These results are robust for bull, bear, volatile, and calm markets and are generally of similar magnitude for stocks with low or high information uncertainty. Furthermore, the documented anomalies are at least as strong when applied to the 100 largest U.S. stocks. Exploiting the option information measures requires an extremely high turnover. Therefore, all profitability is estimated to be consumed by transaction costs in our investable universe. However, more than half the documented profitability persists for a strategy based on only the 100 largest stocks when simple steps are taken to control the transaction costs of managing the portfolio. The net return is economically strong and statistically significant at more than 7% a year for the long–short portfolio. These findings lead us to conclude that the documented strategies are exploitable by practitioners.

Data and Option Market Measures

We first lay out our data sample, the option measures we used, and the descriptive statistics of our sample and variables.

Sample. To examine the investability of the option information strategies, we limited our universe to the 1,250 largest stocks in the S&P/Citigroup U.S. Broad Market Index over January 1996–October 2009. This universe represented a minimum market capitalization of approximately US$1 billion in 2009, resulting in highly liquid stocks that could be easily traded at limited transaction costs. This requirement made the stocks investable for many equity investors. We obtained data on daily stock returns, including dividends and market capitalizations, from the FactSet Global Prices database and accounting data from Capital IQ Compustat.

For the stocks in this universe, we extracted option data from OptionMetrics, which contains end-of-day bid and ask quotes, open interests, and trading volumes for all equity options traded in the United States. For all individual U.S. equity options, OptionMetrics calculates implied volatilities and Greeks by using a binominal-tree model based on the algorithm of Cox, Ross, and Rubinstein (1979). This algorithm copes with discrete dividend payments and the possibility of early exercise. We used the following filters on all options to ensure that we selected liquid and heavily traded options containing the most reliable information. We filtered out options with zero volume or open interest. Because most activity in options is concentrated in the short end, we selected options with a remaining maturity of approximately one month by requiring a maturity of 10–40 trading days. We followed Xing et al. (2010) in separating options into at-the-money (ATM) and out-of-the-money (OTM) options. We defined a put or call option as ATM when the ratio of the strike price to the stock price was between 0.95 and 1.05 and a put option as OTM when the ratio was lower than 0.95 but higher than 0.80. When multiple options fell into the same group, we selected options with moneyness closest to 1.00 (ATM) or 0.95 (OTM).[2]

Option Measures. The first option market measure we used was the OTM volatility skew, which is thought to reflect worries about negative price movements—for example, those arising from an informational advantage (Xing et al. 2010). Gârleanu, Pedersen, and Poteshman (2009) argued that with respect to companies of which investors have relatively pessimistic perceptions, investors tend to buy put options for either protection against or speculation on future stock price drops. This increase in the demand for put options leads to a higher price and implied volatility, yielding a steeper volatility smile. Therefore, stocks with a high volatility skew should underperform stocks with a lower skew. Following Xing et al. (2010), we computed the OTM volatility skew as follows:

$$SKEW_{i,t}^{OTM} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMC}, \tag{1}$$

where $IV_{i,t}^{OTMP}\left(IV_{i,t}^{ATMC}\right)$ denotes the implied volatility of the OTM put (ATM call) option on stock i in week t. To compute the measure, we used the weekly average of the IV variables to reduce the effect of noise and required at least two nonmissing values during the past five days.

The second measure we used was the realized (historical) versus implied volatility spread, which is thought to capture the volatility risk of a stock; Bali and Hovakimian (2009) showed that stocks with a higher spread between realized and implied volatility have higher volatility risk. Moreover, Bakshi and Kapadia (2003a, 2003b) showed that the realized versus implied volatility spread bears a negative volatility risk premium. Thus, stocks with a high realized versus implied volatility spread should underperform. We measured the realized versus implied volatility spread by the difference between the realized volatility of the past 20 daily stock returns and the implied volatility:

$$RVIV_{i,t} = RV_{i,t} - IV_{i,t}^{ATM}, \tag{2}$$

where $RV_{i,t}$ is the realized volatility of stock i measured in week t and $IV_{i,t}^{ATM}$ is the average of the implied volatility of the ATM call and ATM put options on stock i in week t. As before, we used a weekly average of the IV values to reduce the effect of noise. To compute the measure, we required at least two nonmissing values during the past five days.

The third measure we used was the ATM volatility skew, which relates to the trading activity of informed investors and jump premiums. Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) argued that more informed trading activity of pessimistic (optimistic) investors and lower (higher) positively priced jump risk lead to higher (lower) implied volatilities of ATM put options as compared with ATM call options. Stocks with a high ATM volatility skew should thus underperform. We took the difference between the implied volatilities of ATM put and call options as our ATM volatility skew measure:

$$SKEW_{i,t}^{ATM} = IV_{i,t}^{ATMP} - IV_{i,t}^{ATMC}, \tag{3}$$

where $IV_{i,t}^{ATMP}$ denotes the implied volatility of the ATM put option on stock i in week t. As before, we took the weekly average of the IV variables to reduce the effect of noise, and we required at least two nonmissing values during the past five days to compute the measure.

The fourth measure we used was the change in the ATM volatility skew, which is thought to reflect the change in informed trading. Cremers and Weinbaum (2010) argued that an increase in the informed trading activity of pessimistic (optimistic) investors is likely to result in an increasing (decreasing) spread between the implied volatilities of ATM put and call options, which should predict lower (higher) stock returns. Because we focused on a weekly frequency, we computed the change in the ATM volatility skew variable as the weekly change in the volatility spread between the ATM put and call options:[3]

$$\Delta SKEW_{i,t}^{ATM} = SKEW_{i,t}^{ATM} - SKEW_{i,t-1}^{ATM}. \qquad (4)$$

With respect to our four option measures, note that we prefer to use a consistent methodology for all of them. Therefore, our definitions of the measures differ slightly from the ones used in previous studies owing to the use of different option filters, the use of weekly averages to reduce the effect of noise, and our focus on weekly investment frequencies. For example, besides the use of different option filters in other studies, our measures for *RVIV* and $SKEW^{ATM}$ differ from the measures proposed by Bali and Hovakimian (2009), who used an average of all near-the-money call and put options at the end of a month. Similarly, our measures for $SKEW^{ATM}$ and $\Delta SKEW^{ATM}$ differ from the ones put forward by Cremers and Weinbaum (2010), who used the open-interest weighted average difference between the implied volatilities of the call and put options across several option pairs with the same strike and maturity and its daily change. These choices, however, are unlikely to be important because our definitions capture the same economic ideas as the original measures proposed in the earlier studies.

Descriptive Statistics. Panel A of **Table 1** presents the coverage statistics of the option measures averaged for each week in our sample (average), at the start of our sample (start), and at the end of our sample (end).[4] The following points emerge. First, the coverage for $SKEW^{OTM}$ is the lowest—with, on average, 619 of the 1,250 stocks covered—because the availability of out-of-the-money option data is lower compared with at-the-money option data. Second, the coverage increases over our sample for all option measures. Third, the coverage is already substantial at the start of our sample period, with coverage between 317 stocks (for $SKEW^{OTM}$) and 625 stocks (for *RVIV*). Fourth, when we investigated a strategy that combines the option variables, we required that at least one option variable be available, which led to an average coverage of 901 stocks, starting with 690 stocks at the beginning and 1,045 stocks at the end of our sample period.[5]

Panel B of Table 1 reports the descriptive statistics for the stocks and options in our universe. It shows the time-series averages of the cross-sectional means, standard deviations, and quartiles. The first two rows report the market capitalizations (market value of equity, or ME) and book-to-market ratios (B/Ms) of the companies in our universe for which option information is available. As expected, the companies in our universe are large compared with the average company listed on the NYSE/Amex/NASDAQ. The average (median) market capitalization equals US$9.19 billion (US$3.33 billion), compared with average (median) values of US$2.19 billion (US$0.17 billion) for all stocks on the NYSE/

Table 1. Descriptive Statistics, January 1996–October 2009

	$SKEW^{OTM}$	*RVIV*	$SKEW^{ATM}$	$\Delta SKEW^{ATM}$	All
A. Stock coverage					
Average	619	842	795	708	901
Start	317	625	494	387	690
End	865	1,012	999	924	1,045
	Mean	St. Dev.	25%	50%	75%
B. Summary statistics					
ME ($ billions)	9.19	16.80	1.62	3.33	8.66
B/M	0.37	0.24	0.20	0.33	0.50
$SKEW^{OTM}$ (%)	4.72	3.47	2.50	4.23	6.41
RVIV (%)	–0.82	10.67	–7.54	–1.84	4.56
$SKEW^{ATM}$ (%)	0.79	2.08	–0.31	0.62	1.74
$\Delta SKEW^{ATM}$ (%)	0.00	2.15	–1.12	0.00	1.12
	$SKEW^{OTM}$	*RVIV*	$SKEW^{ATM}$	$\Delta SKEW^{ATM}$	
C. Rank correlations					
$SKEW^{OTM}$	100%				
RVIV	2	100%			
$SKEW^{ATM}$	43	1	100%		
$\Delta SKEW^{ATM}$	21	1	53	100%	

Amex/NASDAQ and US$7.53 billion (US$2.13 billion) for all stocks on the NYSE/Amex/NASDAQ with information available from OptionMetrics over the same period. The next rows describe our option measures: On average, $SKEW^{OTM}$ is 4.72%, $RVIV$ is negative (–0.82%), $SKEW^{ATM}$ is positive (0.79%), and $\Delta SKEW^{ATM}$ is 0.00%. All these measures display substantial variability over the cross section, with average standard deviations between 2.08% ($SKEW^{ATM}$) and 10.67% ($RVIV$).

Panel C of Table 1 reports the time-series averages of the cross-sectional mean Spearman rank correlations between our four option price variables. All the variables have low to moderate correlations with each other. Most notably, high values of $SKEW^{ATM}$ tend to coincide with high past-week $\Delta SKEW^{ATM}$—witness their positive correlation of 53%. Similarly, $SKEW^{ATM}$ values tend to correlate with $SKEW^{OTM}$ values (43%), as was also found recently by Doran and Krieger (2010).[6] These numbers suggest the possibility of information overlap in the option variables, which we discuss in our analyses reported later in the article. The overlap, however, does not affect our conclusions concerning the exploitability by practitioners of publicly available option market information.

Methodology

To evaluate the information contained in option prices, we used the following procedure. Every Tuesday, we measured each variable given the latest close information from the option market.[7] Subsequently, we sorted companies on each variable and formed five quintile portfolios, from Quintile 1 (Q1) to Quintile 5 (Q5). Q1 (Q5) contained the stocks with the lowest (highest) variable value, for which we expected the highest (lowest) return. We computed the equally weighted returns of these portfolios over the following week because (1) we had no microcaps in our sample (which are generally hard to invest in and are thus less attractive to practitioners) and (2) equally weighted portfolios are generally better diversified in a sample of large-cap stocks.[8] We stress, however, that the conclusions of our analyses are unchanged by computing value-weighted returns, as reported in Appendix A.[9]

In our empirical analyses, we included a one-day lag between the strategy signals and portfolio construction. Therefore, we bought stocks at Wednesday close prices. This implementation lag allowed us sufficient time to implement the portfolios (as it would for less technologically advanced investors) and to avoid spurious findings caused by nonsynchronous trading between options and stocks owing to slightly different closing times of the exchanges (see Battalio and Schultz 2006). We rebalanced the portfolios every week and calculated their returns in excess of the risk-free rate and their outperformance relative to the equally weighted market portfolio. Moreover, we computed the performance of a long–short portfolio as the return difference between the top (Q1) and bottom (Q5) quintiles.

Subsequently, we controlled for market, size, value, and momentum exposures by correcting the portfolio returns for the market return, the Fama–French (1992, 1993) size (SMB) and book-to-market (HML), and the Carhart (1997) momentum (UMD) factors (obtained from Kenneth French's website[10]). The resulting alpha, or estimated abnormal return, of portfolio j is the constant α_j in the regression

$$\begin{aligned} r_j &= \alpha_j + \beta_j r_m + s_j SMB + h_j HML \\ &\quad + u_j UMD + \varepsilon_j, \end{aligned} \tag{5}$$

where r_j is the excess return of portfolio j, r_m is the excess return on the market portfolio, and β_j, s_j, h_j, and u_j are the estimated factor exposures. In addition, we computed CAPM alphas by including only the excess market return in Equation 5.[11]

Furthermore, we conducted Fama–MacBeth (1973) regressions to examine the predictive power of the variables while controlling for other return-predicting variables. Each week, we first estimated a cross-sectional regression of stock returns on the predicting variables to obtain estimated effects (slope coefficients) of the tested variables. To ensure comparability across variables and to limit the influence of outliers, we standardized each variable each week (using the approach described in the next paragraph). In the second stage, we averaged the slope coefficients over time and calculated their t-statistics. We corrected the t-statistics for heteroscedasticity and autocorrelation by applying Newey–West (1987) standard errors.

After studying the predictive power of each of the four variables, we tested their joint profitability (before and after transaction costs) in an aggregate option information strategy. To that end, we transformed the values of each variable into a cross-sectionally standardized score (Z-score) that is comparable across variables. More specifically, we constructed the Z-score of a variable by subtracting its cross-sectional median from the values of the variable and dividing by its median absolute deviation. We used the median and the median absolute deviation instead of the mean and the standard deviation to limit the influence of outliers. We further reduced the effect of outliers by winsorizing the Z-scores at values of ±3. Subsequently, we obtained the combined Z-score as the simple, naive average of all variables[12] and ranked the stocks into quintile portfolios by following the same methodology that we used for each variable.

Results

In presenting our results on the relevance of the public information contained in option prices, we first consider the portfolio sorts based on each variable in isolation. We then show the results of the Fama–MacBeth (1973) cross-sectional company-level regressions that control for other factors that may affect returns, followed by the results of a simple combined option information strategy. Next, we look at the performance over different market conditions, as well as the interaction between the combined option information strategy and information uncertainty. Finally, we examine the profitability of our option information strategy with respect to transaction costs to determine whether our findings are caused by nonexploitable return patterns.

Individual Portfolio Sorts. Table 2 reports the results of sorting each of our option variables into five portfolios and computing the subsequent weekly returns. For each variable, Table 2 shows the average annualized excess geometric returns and Sharpe ratios for the quintiles. For both the long–short and the quintile portfolios, it also shows the outperformances relative to the general equity market and information ratios as defined by the ratio of outperformance and the volatility of outperformance. In addition, it reports the annualized alphas relative to the market model (CAPM alpha) and the four-factor model (4F alpha). Quintile 1 (Q1) contains the stocks that rank lowest on a measure, whereas Quintile 5 (Q5) contains the stocks that rank highest on a measure. Hence, Q1 comprises stocks with the lowest OTM volatility skew, the lowest realized versus implied volatility spread, the lowest ATM volatility skew, and the lowest change in the ATM volatility skew; therefore, we expect Q1 to generate higher returns than Q5. **Figure 1** shows the cumulative performance of the long–short portfolios over time.

Panel A of Table 2 reveals that stocks with the lowest (highest) $SKEW^{OTM}$—that is, the lowest (highest) crash worries—typically experience the highest (lowest) returns. The Quintile 1 portfolio generates, on average, 5.46% a year over the risk-free rate (3.23% over the market), decreasing to –1.87% (–3.96%) for the Quintile 5 portfolio and resulting in an annual return of 7.48% for the Q1–Q5 long–short portfolio. These results are in line with those reported by Xing et al. (2010) for a different universe over 1996–2005 and are both economically and statistically significant. The resulting 4F alpha (CAPM alpha), or abnormal return, is 7.96% (7.49%). Hence, market beta, size, value, and momentum effects cannot explain the observed return spread. Figure 1 shows that the performance is economically strong in the early years of our sample, weaker in the middle years, but economically strong again during the later years of our sample period (2005–2009), thereby providing out-of-sample evidence of the idea put forth by Xing et al. (2010) regarding an investable universe.

As shown in Panel B of Table 2, stocks with the lowest (highest) $RVIV$—that is, the lowest (highest) volatility risk—typically experience the highest (lowest) returns. The Quintile 1 portfolio generates, on average, an excess return of 5.02% a year and an outperformance over the market of 1.06%. The returns decrease to an excess return of –2.36% and an outperformance of –6.04% for the Quintile 5 portfolio. These outcomes result in an economically and statistically significant return of 7.56% a year for the long–short portfolio, which is the highest of the four strategies investigated. The resulting 4F and CAPM alphas are a highly significant 7.06% and 9.13%, respectively, suggesting that market, size, value, and momentum effects can explain only a small fraction of the observed return spread. Our findings confirm the idea of Bali and Hovakimian (2009) for an investable universe that extends the sample beyond December 2004. The top line in Figure 1 shows that the performance is strongest during their sample period but is also positive in subsequent years.[13]

Panel C of Table 2 reveals that stocks with the lowest (highest) $SKEW^{ATM}$ (i.e., the least pessimistic informed trading or highest jump risk premiums) generally experience the highest (lowest) returns. The Quintile 1 portfolio generates, on average, 6.83% a year over the risk-free rate (2.81% over the market), decreasing to 0.42% (–3.37%) for the Quintile 5 portfolio. These outcomes result in a highly economically and statistically significant annual return of 6.40% for the Q1–Q5 portfolio. As with $SKEW^{OTM}$ and $RVIV$, the returns on this portfolio—with a 4F alpha (CAPM alpha) of 7.96% (6.51%)—cannot be explained by market, size, value, or momentum exposures. These results extend the ideas of Bali and Hovakimian (2009) and Cremers and Weinbaum (2010) to a well-investable universe. However, Cremers and Weinbaum's results deteriorated over the later part of their sample period. Figure 1 shows that the performance is economically strong in the earliest years of our sample, weak around the bursting of the tech bubble, but economically strong again in

Table 2. Portfolio Returns of Individual Option Market Variables, January 1996–October 2009

Statistic	Q1	Q2	Q3	Q4	Q5	Q1–Q5
A. $SKEW^{OTM}$						
Excess return (%)	5.46	4.18	2.36	0.34	–1.87	
Sharpe ratio	0.21	0.18	0.10	0.01	–0.08	
Outperformance (%)	3.23**	1.97*	0.18	–1.79*	–3.96**	7.48***
Information ratio	0.58	0.45	0.05	–0.44	–0.67	0.76
CAPM alpha (%)	3.38	2.08	0.23	–1.71	–3.86*	7.49***
4F alpha (%)	2.87*	1.40	–0.01	–2.13	–4.73***	7.96***
B. *RVIV*						
Excess return (%)	5.02	6.56	5.79	3.69	–2.36	
Sharpe ratio	0.22	0.32	0.27	0.16	–0.08	
Outperformance (%)	1.06	2.54*	1.81	–0.22	–6.04**	7.56*
Information ratio	0.16	0.47	0.38	–0.05	–0.54	0.49
CAPM alpha (%)	2.96	4.47***	3.68***	1.57	–4.13	9.13***
4F alpha (%)	2.02	3.12**	2.52**	0.89	–3.10	7.06**
C. $SKEW^{ATM}$						
Excess return (%)	6.83	6.97	3.52	1.62	0.42	
Sharpe ratio	0.28	0.31	0.16	0.07	0.02	
Outperformance (%)	2.81**	2.95***	–0.38	–2.21**	–3.37***	6.40***
Information ratio	0.61	0.82	–0.11	–0.67	–0.73	0.91
CAPM alpha (%)	4.63***	4.70***	1.37	–0.48	–1.58	6.51***
4F alpha (%)	4.93***	4.25***	0.59	–1.47	–2.66	7.96***
D. $\Delta SKEW^{ATM}$						
Excess return (%)	5.55	4.92	4.16	4.05	0.11	
Sharpe ratio	0.22	0.22	0.19	0.18	0.00	
Outperformance (%)	1.67	1.06	0.32	0.22	–3.58***	5.45***
Information ratio	0.35	0.28	0.08	0.06	–0.74	0.78
CAPM alpha (%)	3.37*	2.81*	2.05	1.91	–2.08	5.69***
4F alpha (%)	3.00*	2.21	1.10	1.36	–2.25	5.52***

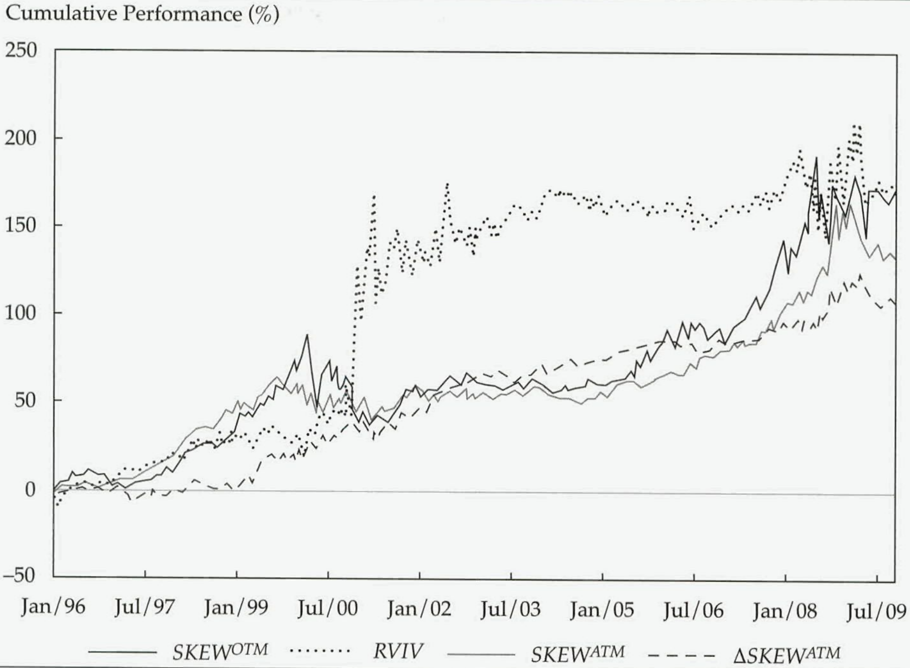
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

the more recent years not considered by the Bali–Hovakimian and Cremers–Weinbaum studies.

Finally, Panel D of Table 2 contains the results of our fourth variable, $\Delta SKEW^{ATM}$, which proxies the change in informed trading. We would expect an increase (decrease) in the informed trading activity of optimistic (pessimistic) investors to lead to higher subsequent returns. Indeed, we found that the Quintile 1 portfolio generates higher returns than the Quintile 5 portfolio (5.55% versus 0.11%), which results in an economically and statistically significant return of 5.45% a year for the Q1–Q5 long–short portfolio. As with the previous variables, the returns on this portfolio, with a 4F alpha (CAPM alpha) of 5.52% (5.69%), are not explained by market, size, value, or momentum exposures. Figure 1 shows that the performance is flat in the early years of our sample but steady and economically positive since 1999, including the post–Cremers and Weinbaum sample period.

These results show that the option strategies deliver significant results when applied to an investable universe of large-cap stocks. Apart from *RVIV*, the strategies provide stable performance in the recent crisis period. Furthermore, Figure 1 shows that the return patterns of the four variables are quite different from each other, indicating potential diversification benefits when combined into one option strategy. A correlation analysis confirms this finding: The correlations (not presented in tabular form) between the weekly Q1–Q5 quintile portfolio returns are low to moderate, ranging from –3% (between *RVIV* and $SKEW^{OTM}$) to 44% (between $SKEW^{ATM}$ and $SKEW^{OTM}$).

Figure 1. Cumulative Performance of Individual Option Market Variables, January 1996–October 2009



Company-Level Regressions. The previous results reveal that forming portfolios on the basis of each of the four option price variables would have generated significant profits. To control for hitherto excluded variables that may affect returns and to test for the option price variables' joint significance, we continued our analysis with Fama–MacBeth (1973) regressions.

Table 3 reports the results in terms of estimated standardized coefficients and their significance. We annualized all coefficients by multiplying by 52 so that the values represent the annualized return changes caused by a one-standard-deviation shock to the underlying variables. Although the same picture emerges from Models 1–5, for the sake of brevity we will focus primarily on Models 6–10, which include the control variables logarithm of the market capitalization, book-to-market ratio, nine-month momentum excluding the last month (MoM), market beta (beta), and short-term reversal (STR). We first considered the company-level regressions by using each variable in isolation. The results confirm our earlier portfolio results. Models 6–9 show that, in isolation, each option variable displays statistically significant negative predictive power for subsequent weekly stock returns after correcting for control variables. In economic terms, the coefficients also imply strong predictive power, with a three-standard-deviation change in the variables (roughly comparable to the difference between the top and bottom portfolios), resulting in a change in annualized returns of 4.11% to 5.64%.

Moreover, the regression results also reveal that the option strategies are substantially different from the other well-known stock selection strategies: momentum, reversal, beta, size, and value. This may not come as a complete surprise given that the motivation of the option variables that we studied (i.e., volatility risk, jump risk, and informed trading) differs fundamentally from the motivation of the traditional stock selection strategies—that is, herding, under- and overreaction, (distress) risk, and under- and overvaluation.

Next, we considered the effect of all option price variables jointly. Model 5 of Table 3 reveals that all option variables jointly contain predictive information for stock returns, with a significant R^2 of 2.6%. Similarly, the R^2 of Model 10 (which includes all control variables) is 13.7%, compared with R^2s of 11.8%–12.3% for Models 6–9, in which only a single option measure is considered. The variables $RVIV$, $SKEW^{ATM}$, and $\Delta SKEW^{ATM}$ remain significant and of roughly similar magnitude to those in Models 6–9. In contrast, the coefficient of $SKEW^{OTM}$ becomes insignificant and positive. This result may be caused by the correlation between the $SKEW^{ATM}$ and $SKEW^{OTM}$ measures. In fact, Doran and Krieger (2010) noted that the $SKEW^{OTM}$ of Xing et al. (2010) consists partly of $SKEW^{ATM}$ and argued for using

$$\begin{aligned} DKSKEW_{i,t}^{OTM} &= IV_{i,t}^{OTMP} - IV_{i,t}^{ATMP} \\ &= SKEW_{i,t}^{OTM} - SKEW_{i,t}^{ATM} \end{aligned}$$

Table 3. Company-Level Regressions, January 1996–October 2009

Variable	1	2	3	4	5	6	7	8	9	10
Constant	9.15	10.53*	10.43*	10.19*	9.99*	9.50*	11.13**	11.43**	11.27**	9.90*
$SKEW^{OTM}$	–1.93***				–0.58	–1.37***				0.19
$RVIV$		–1.93*			–2.60**		–1.68***			–2.06***
$SKEW^{ATM}$			–1.74***		–0.87			–1.88***		–1.41**
$\Delta SKEW^{ATM}$				–1.45***	–1.25**				–1.40***	–1.07**
log(ME)						–0.08	–0.68	–0.98	–0.99	–0.55
B/M						0.88	0.92	0.94	0.96	0.74
MoM						1.47	1.39	1.52	1.39	1.38
Beta						–2.29	–1.96	–2.38	–2.26	–1.76
STR						–3.63***	–3.30***	–3.42***	–3.82***	–3.33***
R^2	0.5%	1.1%	0.2%	0.3%	2.6%	12.3%	12.0%	11.8%	12.1%	13.7%
N	619	842	795	708	546	607	825	780	697	536

Notes: This table shows the results of cross-sectional regressions of weekly excess returns under the Fama–MacBeth (1973) methodology that controls for company characteristics. It reports the average estimated coefficients, R^2, and average number of cross-sectional stock observations for each model.

*Significant at the 10% level under Newey–West adjusted standard errors.
**Significant at the 5% level under Newey–West adjusted standard errors.
***Significant at the 1% level under Newey–West adjusted standard errors.

instead to capture worries about negative price movements. Interestingly, their findings reveal that higher values of the latter measure result in higher, not lower, returns.

To examine this effect in more detail, we reran the individual portfolio sort and Fama–MacBeth regressions by using $DKSKEW^{OTM}$, which has a correlation of 75% with $SKEW^{OTM}$. The unreported results from these analyses are qualitatively similar to those reported in Table 3. In addition, we cannot confirm the positive relation between values of $DKSKEW^{OTM}$ and subsequent returns, as documented by Doran and Krieger (2010). In fact, using a portfolio sort, we found a negative (but still insignificant) coefficient in both the univariate and the multivariate Fama–MacBeth regressions and an insignificant long–short return (4F alpha) of –2.65% (–2.04%).

To conclude, the Fama–MacBeth regressions confirm our hypothesis that information contained in publicly available option prices predicts returns on the underlying stocks, even after controlling for a set of other return-predicting variables.

Combined Option Information Strategy. These results reveal the predictive power of the option variables for stock returns over the subsequent week. From an investor's perspective, the joint value of the option market information variables is especially interesting. Therefore, we aggregated the option variables into a simple combined option information strategy, using the procedure outlined earlier.

Even though not all option variables were individually significant in the multivariate Fama–MacBeth regressions, we chose to combine all four of our option variables because all were shown to have substantial predictive power in the individual portfolio sorts and their strategy returns were not highly correlated.[14] **Table 4** reports the results. Sorting stocks on the basis of the combined option information measure leads to large spreads in subsequent weekly returns, larger than observed for each individual option market variable. The Quintile 1 portfolio generates, on average, 8.09% a year over the risk-free rate (4.37% over the market), monotonically decreasing to –1.64% (–5.03%) for the Quintile 5 portfolio. These outcomes result in a highly economically and statistically significant return of 9.90% a year for the Q1–Q5 long–short portfolio, with an information ratio of 1.13. The 4F and CAPM alphas reveal similar results, with values of 10.06% and 10.09%, respectively. **Figure 2** shows the cumulative performance of the long–short portfolio over time. Apart from a drawdown in 2009, the strategy delivers a strong, increasingly stable outperformance, even in the recent, previously out-of-sample crisis years.[15]

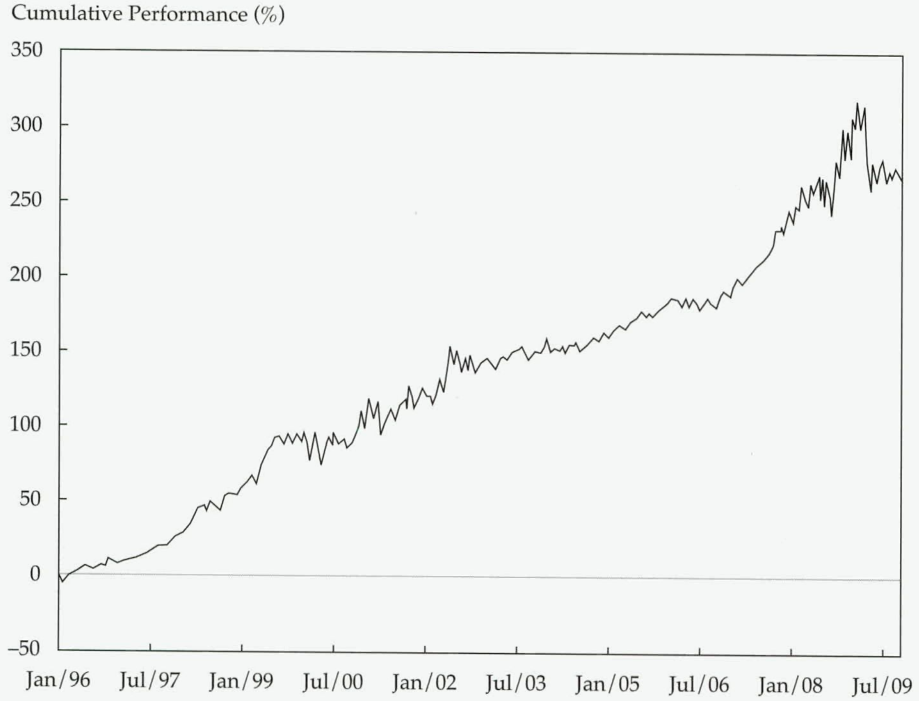
Robustness Analyses. Our results have shown that the long–short portfolio based on the combined option information strategy yields economically and statistically significant returns. We further analyzed the robustness of these findings by examining the portfolio performance in various market conditions and by investigating the interaction of the combined strategy with various measures of information uncertainty.

Table 4. Portfolio Returns of the Combined Option Information Strategy, January 1996–October 2009

Statistic	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Excess return (%)	8.09	6.17	3.18	1.85	–1.64	
Sharpe ratio	0.34	0.29	0.15	0.08	–0.06	
Outperformance (%)	4.37***	2.52**	–0.38	–1.66*	–5.03***	9.90***
Information ratio	0.92	0.64	–0.11	–0.49	–0.86	1.13
CAPM alpha (%)	5.79***	4.01***	1.10	–0.24	–3.71*	10.09***
4F alpha (%)	5.38***	2.78**	0.20	–0.90	–4.03**	10.06***

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Figure 2. Cumulative Performance of the Combined Option Information Strategy, January 1996–October 2009



Performance in various market conditions. To examine the stability of the combined option strategy's performance in various market conditions, we split our sample into (1) bull and bear markets on the basis of positive and negative monthly market returns and (2) volatile and calm markets on the basis of the Chicago Board Options Exchange Volatility Index being above or below its median value. **Table 5** reports the results. The performance of the strategy is strong in both bull and bear markets (although even stronger in bear markets), with top-minus-bottom returns (4F alphas) of 11.94% (11.82%) in bear markets versus 8.57% (9.34%) in bull markets. The results are also stable across volatility regimes, with the strongest performance in volatile markets. The top-minus-bottom returns (4F alphas) are 11.34% (10.67%) in volatile markets versus 8.36% (6.19%) in calm markets. These results confirm that the strategy works not only over the whole sample but also in various subsamples and market environments.

Table 5. Performance in Various Market Conditions, January 1996–October 2009

Statistic	Bull	Bear	Volatile	Calm
Outperformance (%)	8.57***	11.94***	11.34***	8.36***
Information ratio	1.20	1.32	1.15	1.57
CAPM alpha (%)	8.81***	11.25***	10.33***	6.20***
4F alpha (%)	9.34***	11.82***	10.67***	6.19***

***Significant at the 1% level.

The impact of information uncertainty. Next, we analyzed how the profitability of the combined option information strategy interacts with information uncertainty. In a recent paper, Zhang (2006) argued and found that behavioral biases tend to strengthen when information uncertainty is higher and that, as a consequence, momentum profits are higher among stocks surrounded with high information uncertainty than among low-uncertainty stocks. Information uncertainty may also amplify the combined option information strategy. Part of its predictive effect may be due to the signaling of private information, and the advantage of private information may be affected by the uncertainty regarding the usefulness and value of the information.

To investigate whether the results of our combined option information strategy are indeed affected by information uncertainty, we performed the following analysis. We ranked the stocks with option information available in five quintiles on the basis of three measures of information uncertainty: market capitalization, past 52 weeks' volatility, and the number of analysts covering the stock. Within each of these groups, we sorted the stocks on our combined option signal and examined the performance of a long–short quintile portfolio. The results are presented in **Table 6**. Lower market capitalization, higher volatility, and a lower number of analysts covering a stock indicate higher information uncertainty. The combined option information strategy yields a significant outperformance and 4F alpha for all long–short portfolios for all three information uncertainty measures. In addition, the last column of Table 6 (HML; containing the difference in the long–short returns between the high and low groups) reveals that the profitability of the combined option information strategy is not significantly greater for high versus low information uncertainty portfolios. For example, the long–short combined option information strategy has an outperformance (4F alpha) of 13.87% (14.62%) for the quintile of smallest stocks in our sample versus 12.85% (13.05%) for the quintile of largest stocks. These results suggest that information uncertainty does not amplify the profitability of the combined option variables.

The Impact of Transaction Costs. Our analyses have demonstrated that public option market information contains valuable information for equity investors. From an investor's perspective, it is important to know whether this conclusion also holds after accounting for transaction costs. In fact, several recent studies have shown that many anomalies are unprofitable after transaction costs (see, e.g., Lesmond, Schill, and Zhou 2004; Avramov, Chordia, and Goyal 2006). Therefore, we next examined the net profitability of our combined option information strategy.

To that end, we needed an estimate of the transaction costs per individual stock. Researchers and practitioners commonly use the model of Keim and Madhavan (1997), who regressed total transaction

Table 6. Double Sorts on Information Uncertainty Measures, January 1996–October 2009

Statistic	Low	2nd	3rd	4th	High	HML
A. Market capitalization						
Outperformance (%)	13.87***	8.10**	9.96***	8.27***	12.85***	–0.87
Information ratio	0.93	0.56	0.72	0.65	1.00	–0.06
CAPM alpha (%)	14.22***	8.97***	10.55***	9.03***	13.01***	0.49
4F alpha (%)	14.62***	10.48***	9.78***	8.83***	13.05***	0.21
B. Volatility						
Outperformance (%)	4.83***	5.78***	11.41***	13.44***	10.90**	5.76
Information ratio	0.71	0.65	1.08	0.99	0.59	0.32
CAPM alpha (%)	5.03***	5.91***	11.51***	13.23***	12.05**	7.06
4F alpha (%)	4.96***	6.07***	11.67***	14.98***	11.00**	6.09
C. Number of analysts						
Outperformance (%)	12.11***	10.29***	12.01***	7.13*	11.66***	–0.41
Information ratio	0.82	0.72	0.91	0.51	0.78	–0.02
CAPM alpha (%)	12.79***	10.81***	12.57***	8.61***	12.08***	1.49
4F alpha (%)	14.6***	9.25***	12.85***	7.63**	11.64***	–0.81

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

costs (including commissions paid and an estimate of price impact) for trading NYSE/Amex stocks in 1991–1993 on several characteristics of the trade and the traded stock. However, as pointed out by de Groot, Huij, and Zhou (2012), the transaction cost estimates resulting from the Keim–Madhavan model should be interpreted with caution when applied to the most recent decades. The reason is that Keim and Madhavan (1997) estimated their model for all stocks with data for 1991–1993 and market microstructures and transaction costs have changed substantially since then. In fact, de Groot et al. (2012) found that the Keim–Madhavan model systematically yields negative cost estimates for a large group of liquid stocks over our sample period. For example, the median single-trip transaction cost estimates of the Keim–Madhavan model for S&P 500 Index stocks are –9 bps over our sample period, substantially *lower* than the 9 bps based on estimates of de Groot et al., which suggests that we would clearly *underestimate* transaction costs (and hence overestimate the net return) when applying the Keim–Madhavan transaction cost estimates to our universe. Furthermore, during our sample period, the transaction cost estimates of de Groot et al. declined for the S&P 500 universe, from median single-trip transaction costs of approximately 12 bps in 1996 to a low of 6.5 bps in 2008, indicating the general increase in liquidity over time.

Therefore, we followed the procedure proposed by de Groot et al. (2012) to estimate each stock's transaction costs. They proposed estimating transaction costs by ranking a stock on the basis of its dollar volume in a given quarter and applying the transaction cost estimates for the matching quarterly dollar-volume-sorted decile portfolio of S&P 1500 or S&P 500 stocks, as presented in their Table 1, Panel B and Table 2, Panel B, respectively. These estimates were obtained from Nomura Securities Co., one of the major brokers in the cash equity market, and include both estimates of commissions and the price impact of trades. The assumed trade size for these estimates is US$1 million per stock by the end of 2009, deflated back in time by 10% a year. Consequently, the estimates are valid for a sizable strategy.[16]

Table 7 presents the results when incorporating transaction costs. The first column of Table 7 reports the results of the long–short combined option information strategy applied to our investable universe, consisting of the largest 1,250 U.S. stocks. Clearly, transaction costs can have a dramatic impact on the profitability of the combined option information strategy owing to a high turnover of 150% a week (compared with a maximum possible turnover of 200% in the case of a complete replacement of the long and the short portfolios). As a result, the outperformance drops from 9.90% a year to –9.88%, suggesting that the strategy is not exploitable.

Because the turnover of the combined option information strategy is very high, we investigated what would happen if we focused only on stocks with the lowest transaction costs. Therefore, we next repeated the same exercise on the extremely liquid universe of the 100 largest stocks in terms of market capitalization—generally the stocks with the highest liquidity and lowest transaction costs. For this universe, de Groot et al. (2012) used average

Table 7. Gross and Net Outperformance of Strategies Based on the Option Information, January 1996–October 2009

	Static Portfolios		Dynamic Portfolios	
Statistic	1,250 Largest	100 Largest	1,250 Largest	100 Largest
Outperformance (%)	9.90***	13.57***	9.84***	12.95***
Information ratio	1.13	0.95	1.07	0.92
Turnover (%)	150	150	97	70
Avg. holding period (days)	6.7	6.7	10.3	14.3
Net outperformance (%)	–9.88	2.39	–4.18	7.61**
Net information ratio	–1.09	0.17	–0.45	0.54
Net CAPM alpha (%)	–9.69	3.48	–3.53	8.53***
Net 4F alpha (%)	–9.87	3.08	–4.00	7.53***

Notes: This table presents the gross and net outperformance of the long–short portfolio with respect to the combined option strategies. The static portfolios contain only stocks that are ranked among the top (bottom) 20% of the universe and are rebalanced every week. The dynamic portfolios are constructed by using an approach that does not directly sell (buy back) stocks that are no longer in the top (bottom) quintile but waits until the day those stocks are ranked among the bottom (top) 20% of stocks.

**Significant at the 5% level.
***Significant at the 1% level.

single-trip transaction costs of approximately 7 bps over our sample period versus 13 bps for the S&P 1500 stocks. The second column of Table 7 shows that the gross outperformance increases to 13.57% a year when applied to these 100 largest stocks. Hence, the gross profitability of the combined option information strategy does not decrease for the largest and generally most liquid and most followed stocks. At the same time, turnover remains similar and, therefore, the impact of transaction costs substantially decreases, from 19.78% to 11.18%, leading to a positive net outperformance of 2.39% a year. Although still sizable in economic terms, this number is not statistically significant.

Still, this analysis deals relatively naively with transaction costs. In fact, portfolio optimization theory prescribes an efficient trade-off of the decay in predictive power versus reduction in transaction costs in order to maximize expected net risk-adjusted performance. We applied this principle by using a simple turnover-reducing portfolio construction approach to the two universes. More specifically, at the beginning of our sample period, we formed a long–short portfolio on the basis of the option strategy signal. Once included in the long (short) portfolio, a stock is held until the day it is ranked the most unattractive (attractive)—that is, has fallen to the bottom (for long positions) or risen to the top (for short positions) quintile. On the day a stock falls out of the portfolio, it is replaced by the most attractive (for long positions) or least attractive (for short positions) stock not yet included in the portfolio. Hence, trades occur only at the moment a stock migrates from the 20% most (least) attractive stocks to the 20% least (most) attractive stocks. This approach not only limits the turnover of the portfolio to stocks that are expected to move strongly in the adverse direction but also ensures that the number of stocks in the portfolio is equal to the number of stocks in the long–short portfolio in the previous analysis.

The results of such a dynamic portfolio are presented in the last two columns of Table 7. Let us first examine this approach in our investable universe of 1,250 U.S. large-cap stocks. Gross outperformance deteriorates marginally: The performance of the 1,250 largest stocks is 9.84% annually (9.90% for the static long–short portfolio). However, turnover decreases by more than one-third, from 150% to 97%, leading to a substantial reduction in transaction costs, from 19.78% to 14.02%. Still, the net outperformance of the strategy is negative (–4.18%). Next, we repeated the same exercise on the extremely liquid universe of the 100 largest stocks (column 4 of Table 7). Again, gross outperformance deteriorates marginally, from 13.57% to 12.95%. Simultaneously, the impact of transaction costs is reduced to a relatively small 5.34%, which leads to an economically and statistically significant outperformance of 7.61% a year and a 4F alpha of 7.53%. Hence, significant outperformance remains when accounting for transaction costs by means of a turnover-reducing approach in a low-transaction-cost universe.[17]

In this analysis, we investigated a long–short strategy and thus might also face shorting costs. The net returns of this long–short strategy are large enough to cover realistic shorting costs of 50–100 bps. As a comparison, D'Avolio (2002) estimated the shorting costs to average 60 bps for a much broader universe. In addition, an investor can reduce, or even avoid, shorting costs by taking active positions based on the combined option information strategy against a certain benchmark index, as commonly done by many institutional equity managers.

To summarize, although the gross return of the combined option information strategy is high, its turnover is also substantial. Therefore, the impact of transaction costs can substantially diminish its net profitability. However, large, significant net returns can be obtained when avoiding stocks with high transaction costs and using turnover-reducing portfolio construction rules. This finding leads us to conclude that publicly available information contained in option prices can be profitably exploited by investors.

Conclusion

We showed that publicly available information extracted from traded equity options contains valuable information for future stock returns. Trading strategies based on worries about negative price movements (i.e., out-of-the-money volatility skew), volatility risk (i.e., realized versus implied volatility spread), informed trading and jump risk (i.e., at-the-money volatility skew), and the change in informed trading (i.e., the change in the at-the-money volatility skew) yield significant returns and alphas. The performances remain significant after correcting for market, size, value, momentum, reversal, and other return-predicting factors. Hence, we found that the option information strategies are substantially different from other well-known stock selection strategies. These findings extend the results of earlier studies to a well-investable universe of liquid U.S. large caps, a universe highly relevant for equity investors. Moreover, a combined option information strategy produces even stronger results, with an annualized performance of around 10%, thereby strengthening the relevance of the publicly available information contained in option prices for equity investors. Although several studies have reported that the predictive power of option market variables decreases over time, we found significant returns also in recent out-of-sample years. These results are robust for bull, bear, volatile, and calm markets and are generally of similar magnitude for stocks with low or high information uncertainty. In addition, the documented anomalies are at least as strong when applied to the 100 largest stocks. We further found that the profitability of the combined option information strategy can be dramatically reduced by transaction costs because exploiting the option information measures requires extremely high turnover. However, the strategy remains highly profitable when focusing on a low-transaction-cost universe and using simple procedures to reduce transaction costs—annual net returns above 7% can be achieved. This finding suggests that information diffuses gradually from the equity option market into the underlying stock market.

We documented that the four option variables are strong predictors of individual stock returns and thus are relevant for practitioners. Interestingly, the option information strategies differ substantially from other well-known stock selection strategies, such as momentum and value, commonly used by practitioners. Finally, one may raise the question whether these effects are expected to persist in the long term. Although time must ultimately answer this question, several points may be worth considering here. First, we provided out-of-sample evidence on the predictive power of the four option variables, suggesting that their profitability is unlikely to be caused by data mining. Second, the explanations for the anomalies (proposed in the earlier studies) are volatility and jump risk compensation and information trading. Although these risks may materialize at some points, their premiums tend to be structural components of the economic system. This may also be argued for the presence of private information. If some investors will possess private information in the future, the question becomes whether they would be willing to express their views in the option market (so that price discovery will take place in that market). The model of Easley, O'Hara, and Srinivas (1998), which provides a theoretical framework for understanding where informed investors will trade, may be useful here. In their model, informed traders who want to maximize profits choose to trade in the option market if the leverage or liquidity in the options is high, if the liquidity in the stock is low, or if there are already many informed investors in the stock market. This model suggests that the option prices that will continue to signal private information are those with high leverage or liquidity and whose stock has low liquidity or a large, informed investor base. Third, these anomalies may have been less well known compared with, for example, value and momentum strategies, but their documentation may promote a greater awareness. This may result in the entrance of new investors into these anomalies, which could decrease their profitability.

We thank David Blitz, Henk Grootveld, and especially Sjoerd van Bekkum for extremely helpful comments.

This article qualifies for 1 CE credit.

Appendix A. Value-Weighted and Decile Portfolio Returns

In this appendix, we report the value-weighted quintile (**Table A1**) and equal-weighted decile (**Table A2**) portfolio returns for each individual option market variable and the combined option information strategy.

Table A1. Value-Weighted Portfolio Returns of Individual and Combined Option Market Variables, January 1996–October 2009

Statistic	Q1	Q2	Q3	Q4	Q5	Q1–Q5
A. $SKEW^{OTM}$						
Excess return (%)	7.82	3.72	0.21	1.44	–2.84	
Sharpe ratio	0.33	0.17	0.01	0.06	–0.11	
Outperformance (%)	5.75***	1.72	–1.72	–0.52	–4.71*	10.98***
Information ratio	0.65	0.28	–0.34	–0.09	–0.48	0.75
CAPM alpha (%)	5.25***	1.39	–2.16	–0.85	–5.12***	11.24***
4F alpha (%)	5.25***	1.54	–1.85	–0.09	–5.04***	11.28***
B. RVIV						
Excess return (%)	7.89	5.78	2.32	1.38	–3.18	
Sharpe ratio	0.34	0.29	0.12	0.06	–0.11	
Outperformance (%)	5.22*	3.15*	–0.22	–1.15	–5.59	11.45**
Information ratio	0.51	0.49	–0.04	–0.21	–0.41	0.60
CAPM alpha (%)	5.45**	3.33**	0.12	–0.98	–5.38**	12.87***
4F alpha (%)	4.95*	2.84	0.17	–0.39	–3.20	10.18**
C. $SKEW^{ATM}$						
Excess return (%)	5.8	4.64	0.34	0.13	0.28	
Sharpe ratio	0.24	0.22	0.02	0.01	0.01	
Outperformance (%)	3.17	2.04	–2.16*	–2.36	–2.22	5.51*
Information ratio	0.39	0.41	–0.45	–0.43	–0.24	0.45
CAPM alpha (%)	3.40	2.19	–2.01	–2.20	–1.93	6.48*
4F alpha (%)	4.91***	2.85**	–1.71	–2.61	–3.22	9.58***
D. $\Delta SKEW^{ATM}$						
Excess return (%)	3.44	3.06	2.57	1.80	–2.76	
Sharpe ratio	0.14	0.14	0.12	0.08	–0.11	
Outperformance (%)	1.13	0.76	0.28	–0.47	–4.94**	6.39**
Information ratio	0.14	0.14	0.06	–0.09	–0.58	0.56
CAPM alpha (%)	1.11	0.72	0.20	–0.57	–5.19***	7.17***
4F alpha (%)	1.62	1.53	0.15	–0.51	–5.44***	8.06***
E. Combined option information						
Excess return (%)	8.45	6.37	1.51	–0.44	–3.79	
Sharpe ratio	0.37	0.31	0.07	–0.02	–0.14	
Outperformance (%)	5.83***	3.80***	–0.94	–2.85*	–6.12**	12.73***
Information ratio	0.78	0.68	–0.19	–0.51	–0.59	0.90
CAPM alpha (%)	5.91***	3.85***	–0.81	–2.80*	–6.17***	13.50***
4F alpha (%)	6.69***	3.37***	–0.60	–2.04	–5.79***	14.10***

Notes: This table shows the portfolio returns of the individual and combined option variables for our universe of 1,250 U.S. large-cap stocks. We show the results of the quintile portfolios (Q1 to Q5) and the long–short portfolio (Q1–Q5) that are constructed by sorting in increasing order on $SKEW^{OTM}$ (Panel A), *RVIV* (Panel B), $SKEW^{ATM}$ (Panel C), $\Delta SKEW^{ATM}$ (Panel D), and four combined option variables (Panel E). The value-weighted portfolios are constructed by using Tuesday close information, implemented with a one-day lag, and held for one week. We report the geometric excess return, Sharpe ratio, outperformance, and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor alphas of the quintile portfolios and report the alphas on an annual basis.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Table A2. Decile Portfolio Returns of the Combined Option Information Strategy, January 1996–October 2009

	Combined Option Information										
Statistic	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1–D10
Excess return (%)	7.92	8.10	7.34	4.92	1.84	4.45	1.82	1.76	0.82	–4.24	
Sharpe ratio	0.31	0.35	0.33	0.23	0.08	0.20	0.08	0.07	0.03	–0.15	
Outperformance (%)	4.20**	4.37***	3.64***	1.30	–1.67	0.85	–1.69	–1.75	–2.66*	–7.53***	12.69***
Information ratio	0.61	0.80	0.69	0.27	–0.36	0.18	–0.36	–0.37	–0.47	–0.88	1.13
CAPM alpha (%)	5.31**	5.37***	4.72***	2.42	–0.63	1.94	–0.66	–0.68	–1.51	–6.57***	12.98***
4F alpha (%)	5.21***	4.64***	3.57**	1.12	–1.65	1.15	–1.53	–1.15	–1.95	–6.77***	13.20***

Notes: This table shows the portfolio returns of the combined option variables for our universe of 1,250 U.S. large-cap stocks. We show the results of the decile portfolios (D1 to D10) and the long–short portfolio (D1–D10) that are constructed by sorting in increasing order on the combined option variables. The equally weighted portfolios are constructed by using Tuesday close information, implemented with a one-day lag, and held for one week. We report the geometric excess return, Sharpe ratio, outperformance, and information ratio of these portfolios on an annual basis. In addition, we estimate the CAPM and four-factor alphas of the decile portfolios and report the alphas on an annual basis.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Notes

1. More specifically, Hong, Torous, and Valkanov (2007) found that information diffuses from several industry stock indices into the remainder of the stock market for up to two months.
2. We also replicated our analysis by using 0.925 as the OTM boundary, which did not change our conclusions.
3. One could argue that our measures are biased toward highly volatile stocks. Therefore, we also investigated a relative (instead of absolute) definition of these variables. Although doing so did not affect our conclusions (reported later in the article), the results were slightly weaker.
4. The start and end figures are very much in line with the lowest and highest coverage percentiles.
5. Note that the requirement that all four variables have available data would lead to a lower average coverage of stocks (546). This additional requirement, however, does not alter our conclusions. Results are available from the authors upon request.
6. Doran and Krieger (2010) noted that $SKEW^{OTM}$ consists partly of $SKEW^{ATM}$ and proposed using $DKSKEW_{i,t}^{OTM} = IV_{i,t}^{OTMP} - IV_{i,t}^{ATMP}$ to capture crash worries. We also investigated their measure, which does not affect our subsequent conclusions about the relevance of publicly available option market information for equity investors. These results are discussed in more detail later in the article.
7. Our results are not driven by the use of Tuesday close information to construct our variables. When we computed our variables for other days of the week, we obtained comparable results.
8. Moreover, for investors who manage long–short portfolios or active portfolios against a benchmark, there is no need to take active positions in line with the market-cap weight of stocks because doing so would imply that the absolute risk-adjusted expected return of large-cap stocks is higher than that of small-cap stocks.
9. In unreported analyses, we also adjusted the raw variables with respect to their industry medians to avoid unintended industry bets (e.g., those caused by negative worries about entire industries). The average returns (available upon request) are generally comparable to those reported here but are mostly at a lower level of volatility.
10. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.
11. Moreover, we also computed three-factor alphas that correct for market, size, and value exposures and five-factor alphas that correct for market, size, value, momentum, and short-term-reversal exposures. These unreported results (available upon request) are in line with those for the CAPM and four-factor alphas.
12. We required a stock to have at least one available option variable in order to compute the average. In addition, when a stock had no coverage on a particular variable, we assigned a zero, neutral Z-score to that variable.
13. Unlike the results for the other variables, the results for *RVIV* improve substantially when controlling for industry exposures, especially during the recent crisis years.
14. We endorse the view that a model with higher in-sample risk–return characteristics may be found. To avoid any in-sample optimization, however, we leave that task to the reader.
15. In addition, we may wonder whether the performance of the combined option information strategy improves if we consider the stocks with stronger signals—for example, by using decile instead of quintile portfolios. These results (reported in Appendix A) are slightly stronger than the quintile results in terms of outperformance and alpha.
16. For example, a strategy that invests an equal amount in each of the 20% most and least attractively ranked stocks in our universe (i.e., the largest 1,250 U.S. stocks) would be able to use US$250 million of capital by the end of 2009 at these transaction costs.
17. We may well wonder how sensitive these results are to our particular choice of rebalancing rules. Comfortably, when we sell (buy) a long (short) position after a stock has migrated to the bottom (top) 50th, 60th, or 70th percentile (instead of the 80th percentile), we also find a substantial reduction in turnover to 142%, 118%, and 95%, respectively, and significant, positive net outperformance (4F alpha) of 11.12% (11.62%), 9.44% (10.47%), and 9.18% (9.14%), respectively, when applied to the largest 100 stocks.

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